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Iterative census-based demand generation for transportation simulations

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ABSTRACT — New fast transportation micro-simulations make it possible to implement systematic computational feedback between travel demand generation (activities generation), route assignment, and a transportation simulation (network loading) while keeping a microscopic resolution throughout the whole process. Microscopic means that each agent (traveller) is represented microscopically. We describe an implementation of such a computational feedback of micro-simulation results into the activities generation. We use the assignment of workplaces to home locations as an example. The workplace assignment is done in a way that the computation self-consistently finds a solution which reflects the trip time distribution from the census for home-to-work trips. Since the results of this can be expected to be reminiscent of the morning traffic, we compare our resulting hourly volumes with field data in Portland/Oregon and also with results of an earlier modelling study done by the Portland Transportation Planning Organization which uses more traditional methods. We find our results encouraging, especially when taking into account the relative simplicity of our assumptions.

keywords: traffic simulation; transportation planning; travel demand generation; activities generation

1 INTRODUCTION

Several groups are developing simulations which can microscopically simulate whole metropolitan areas in faster than real time (e.g. DYNAMIT, 2000; MITSIM, 2000; Mahmassani et al, 1995 (DYNASMART); Rickert, 1998 (PAMINA); Gawron, 1998 (LEGO); Rakha and Van Aerde, 1996 (INTEGRATION); Esser, 1998 (OLSIM)). By “microscopic” we mean that at a minimum, each traveller is individually resolved. Thus, if one can generate detailed travel plans for each individual, these simulations can execute these plans, while recording for example where conflicts in the form of congestion delay the plans.

In consequence, it is only a question of time until it will be easy to couple such models with models of travel demand generation, as has been demanded for many years (e.g. Axhausen, 1990). Such a coupling will probably include a modal-choice-and-routing module (“router”), and it will do systematic feedback iterations between all the modules. That is, the results of the micro-simulation will be fed back into the router again and again until some relaxation with respect to route choice is obtained, and then the result will be fed back into the activities generation module, which will generate new activities which now take into account the slower speeds in the network caused by congestion.

In this paper, we will demonstrate an early implementation of such a computational feedback of the microsimulation into the activities module. In fact, practitioners have often done some version of such a feedback, by adjusting origin-destination matrices in order to move the volume counts of the assignment model closer to reality. There are also computational procedures with respect to assignment models (e.g. Metaxatos et al, 1995). What we will do here is use such a computational procedure in connection with an explicit traffic microsimulation. We will however simplify in several ways: We will use cars as the only mode of travel, we will have trips from home to work as the only demand, and the traffic micro-simulation is rather simplified. We will adjust the simulation against the census trip time distribution. Although this is an early step and we expect much progress in the near future, we will compare our results with existing volume counts in the Portland/Oregon

area. This should serve as a benchmark for future developments.

We will first state the problem (Sec. 2), followed by a description of our approach with respect to demand generation and feedback (Sec. 3). We then discuss related work (Sec. 4), before we move on to our actual study (Sec. 5) and its results (Sec. 6). The paper is concluded by a discussion and a summary.

2 PROBLEM STATEMENT

In general, we want to generate “realistic traffic” via computer simulation. So any simplifications in the following are not the real problems we want to solve, but necessary assumptions to get there. This is standard practice, but it shifts the focus. If we find a solution that does not solve the simplified problem correctly but generates realistic traffic, then this may be an acceptable result for us.

We envisage that such a computer simulation will be a combination of population generation, activities generation, routes assignment, and traffic micro-simulation, coupled via feedback iterations. So what we do in the following essentially is to pick (simple) versions of these modules, embed them into feedback iterations, and try this on real world input data. The research question was twofold: (1) What are the computational issues? (2) How close to reality (or not) does one get with simple assumptions?

We regard the question of the necessary degree of realism in each of these modules as an open problem which will need further research. That question is not treated in this paper. We do not claim that the degree of realism (or not) chosen in any of the modules used for our investigation is the correct degree of realism in order to obtain meaningful results. In particular, we expect that more sophisticated demand generation techniques (e.g. Bowman, in preparation; Doherty and Axhausen, 1998; Arentze et al, 1998) will lead to more realistic results. We do expect, however, that a systematic inclusion of transportation network impedance, as demonstrated in our study, will contribute to better and more robust models.

The problem that we investigate is how to assign workplace locations to workers via using computer simulation. We know from data where people live, and we also know where they work, but we have to match these two sets of data. The problem is similar to the trip distribution step in the four step process. We do this via some strongly simplified assumptions. In particular, we only look at traffic resulting from people driving from home to work. By this, we are neglecting, for example: delivery trucks, people returning from night shifts, travelers using alternative modes of transportation, etc. It is also clear to us that there is much more complexity in the afternoon peak than in the morning peak. Again, our investigation is a demonstration of a computational procedure, not an attempt to obtain the most possible realistic results for a certain field problem.

Having said that, let us describe our scenario. Our scenario area is Portland in Oregon. Our input data are: (a) a description of the Portland transportation network; (b) a synthetic population based on Portland demographic data; (c) a list of workplaces including location and size; (d) the distribution $N_{cns}(T)$ of actually encountered trip times T from home to work by the Portland population; and (e) a distribution of starting times. What we attempt to do is to match workers (who have home locations) and workplaces such that the resulting

traffic yields trip times which, when aggregated, match the census trip times.¹

3 OUR APPROACH

The approach that is maybe closest to what we want to present here are the discrete choice models (Ben-Akiva and Lerman, 1985). As is well known, in that approach the utility V_i of an alternative i is assumed to have a systematic component U_i and a random component η_i . Under certain assumptions for the random component this implies that the probability p_i (called choice function) to select i is

$$p_i = \exp(\beta U_i) / \sum_i \exp(\beta U_i) . \quad (1)$$

p_i could for example represent the probability to accept a workplace that is i seconds away. If i is indeed taken as time, then U_i is negative, and it follows an inverse S-shaped curve starting at zero, being flat for low i , steeper for medium i , and flat again for high i (Bowman, 1998). By this approach, our above location choice problem would be solved by weighting each given workplace according to time-distance i by p_i and then making a random draw in these probabilities. Clearly, for the discrete choice approach one needs to know the function βU_i .

In this paper, we want to present an approach where the “psychological” function βU_i can be obtained from “observed” trip time distributions, using new methods of micro-simulating large geographical regions. The core idea is that an observed trip time distribution $N_{obs}(t)$ can be decomposed into an accessibility part $N_{ac}(t)$ and an acceptance function $f_{ch}(t)$

$$N_{obs}(t) = N_{ac}(t) \times f_{ch}(t) . \quad (2)$$

$N_{ac}(t)$ is the number of workplaces at time-distance t ; $f_{ch}(t)$ is proportional to the probability that a prospective worker will accept this trip time. Thus, apart from normalization f_{ch} is the same as the choice function in discrete choice theory. Our decomposition allows to separate the network specific distribution $N_{ac}(t)$ from the “psychological” trip time acceptance function. In principle, $f_{ch}(t)$ as found via our relaxation method should be the same as when obtained via an estimation of a survey when suitably averaged over the whole population.

Given a micro-simulation of traffic, $N_{ac}(t)$ can be derived from the simulation result. For a given home location (and a given assumed starting time), one can build a tree of time-dependent shortest paths, and every time one encounters a workplace, one adds that to the count for trip time t . The challenge is that this result depends on the traffic: Given the same *geographic* distribution of workplaces, these are farther away in terms of trip time when the network is congested than when it is empty. That is, given $f_{ch}(t)$, we can obtain $N_{ac}(t)$ via micro-simulation, i.e. $N_{ac}(t) = G[f_{ch}]$, where G is the micro-simulation which can be seen as a functional operating on the whole function $f_{ch}(t)$. The problem then is to find the macroscopic (i.e., averaged over all trips) function $f_{ch}(t)$ self-consistently such that

$$N_{obs}(t) = G[f_{ch}](t) \times f_{ch}(t) . \quad (3)$$

¹Since the whole travel of each traveller in our simulation consists of exactly one trip, we will use “trip time” and “travel time” synonymously.

The approach that we use is a regular relaxation technique. We start with a guess for $f_{ch}(t)$ and from there generate $N_{ac}(t) = G[f_{ch}](t)$ via simulation. A new guess for $f_{ch}(t)$ is obtained via

$$f_{ch}^{(n+1)}(t) = N_{obs}(t)/N_{ac}^{(n)}(t) . \quad (4)$$

A fraction f_{act} of all travelers will do their workplace selection again, using the new f_{ch} . $G[.]$ is generated again via micro-simulation, and this is done over and over again until a sufficiently self-consistent solution for $f_{ch}(t)$ is found.

We use real census data for $N_{obs}(t)$ (see “census-100”-curve in Fig. 3; from now on denoted as $N_{cns}(t)$). People usually give their trip times in minute-bins as the highest resolution. Since our simulation is driven by one-second time steps we need to smooth the data in order to get a continuous function instead of the minute-histogram. Many possibilities for smoothing exist; one of them is the beta-distribution approach in Wagner and Nagel (1999). We encountered problems with that particular fit in our approach for small trip times: Since that fit grows out of zero very quickly, the division N_{obs}/N_{ac} had a tendency to result in unrealistically large values for very small trip times. We therefore used a piecewise linear fit with the following properties: (i) For trip time zero, it starts at zero. (ii) At trip times 2.5 min, 7.5 min, 12.5 min, etc. every five minutes, the area under the fitted function corresponds to the number of trips shorter than this time according to the census data.

Obtaining $G[f_{ch}]$ itself via simulation is by no means trivial. It is now possible to micro-simulate large metropolitan regions in faster than real time, where “micro”-simulation means that each traveler is represented individually. We use a simplified queuing type traffic flow model described in Simon and Nagel (1999). However, even if one knows the origins (home locations) and destinations (workplaces), one still needs to find the routes that each individual takes. This “route assignment” is typically done via another iterative relaxation, where, with location choice fixed, each individual attempts to find faster routes to work. At this point we refer to Rickert (1998) and Nagel and Barrett (1997) for detailed information about the route-relaxation procedure; see also Fig. 1 and its explanation later in the text.

Once $f_{ch}^{(n+1)}(t) = N_{cns}(t)/N_{ac}^{(n)}(t)$ is given, the workplace assignment procedure works as follows: The workers are assigned in random order. For each employee the time distances t for all possible household/workplace pairs $[hw]$ are calculated, while the home location h is fixed and taken directly from the household data for each employee. Let t_{hw} be the resulting trip time for one particular $[hw]$ and $n_{wo}(w)$ the number of working opportunities at workplace w . Then, an employee in household h is assigned to a working opportunity at place w with probability

$$p_{hw} \propto n_{wo}(w)f_{ch}(t_{hw}). \quad (5)$$

In addition to work location, home-to-work activity information also includes the times when employees start their trip to work. These are directly taken from the household data.

The complete approach works as follows:

(1) Synthetic population generation: First a synthetic population was generated based on demographic data (Beckman et al, 1996). The population data comprises microscopic information on each individual in the study area like home location, age, income, and family status.

(2) Compute the acceptance function $f_{ch}(T)$. This is done as follows:

(2.1) For each worker i , compute the fastest path tree from his/her home location. Compute the resulting workplace distribution $N_{wp}(i, T)$ as a function of trip time T .²

(2.2) Average over all these workplace distributions, i.e.

$$N_{wp}(T) := \langle N_{wp}(i, T) \rangle_i := (1/N) \sum_i N_{wp}(i, T) , \quad (6)$$

where N is the number of workers, which is by definition also equal to the number of workplaces. $N_{wp}(T)$ is thus equivalent to our earlier $N_{ac}(T)$.

(2.3) Compute the resulting average choice function via

$$f_{ch}(T) \propto N_{cns}(T) / N_{wp}(T) . \quad (7)$$

In addition, a normalization constant needs to be computed such that

$$\sum_T f_{ch}(T) = 1 . \quad (8)$$

(3) Assign workplaces. For each worker we do:

(3.1) Randomly draw a desired trip time T^* from the distribution $f_{ch}(T)$.

(3.2) Compute the time-dependent fastest path tree based on the trip starting time. Find all workplaces which are at or closest to time distance T^* . Select randomly one of them.

(4) Route assignment: Once people are assigned to workplaces, we run the simulation several times (5 times for the simulation runs presented in the paper) while people are allowed to change their routes (fastest routes under the traffic conditions from the last iteration) as their workplaces remain unchanged.

(5) Then, people are reassigned to workplaces, based on the traffic conditions from the last route iteration. That is, we go back to (2).

This sequence, workplace reassignment followed by several re-routing runs, is repeated till the macroscopic traffic patterns remain constant (within random fluctuations) in consecutive simulation runs. For this, we look at the sum of all people's trip times in the simulation and consider the simulation relaxed when this overall trip time has leveled out.

Running this on a 250 MHz SUN UltraSparc architecture takes less than one hour computational time for one iteration including activity generation, route planning, and running the traffic simulator. The 70 iterations necessary for each series thus take about 4 days of continuous computing time on a single CPU.

4 RELATED WORK

The topic of this paper is a computational procedure of how to systematically feedback the results of a route assignment to demand generation. In principle, any route assignment could be used instead of ours. However, since our work are steps towards a completely microscopic

²In contrast to the routing module, no time-dependence was used here although future implementations should do so.

simulation approach, we are primarily interested in simulation-based route assignment and network loading. For this, one needs traffic flow simulations where one is able to follow each vehicle individually. Some simulations which fulfill this requirement besides the queue simulation used in the paper are: PAMINA (Rickert, 1998); the TRANSIMS main micro-simulation (TRANSIMS, 1992); LEGO (Gawron, 1996); INTEGRATION (Rakha and Van Aerde, 1996); DYNASMART (Mahmassani et al, 1995); PARAMICS (1996); MITSIM (Yang, 1997); DYNAMIT (2000); DYNEMO (Schwertfeger, 1987) or VISSIM (2000). Out of these, probably only LEGO, DYNASMART, DYNEMO, and DYNAMIT are fast enough to run iteration series such as ours on a single CPU. Within these four, LEGO is based on a queue model very similar to ours, while the other three use macroscopic equations for the movement of the vehicles.

In terms of re-routing during the route iterations, we use a standard time-dependent fastest path Dijkstra (see, e.g., Jacob et al, in press) based on 15-min link trip time averages. We do however only re-plan a fraction of the population. A widely-used alternative here is to re-plan 100% of the population in each iteration but to use a discrete choice approach approach to spread travelers across different routes (Cascetta and Papola, 1998; Bottom, in preparation). Besides different theoretical properties, these approaches also have different computing complexities. The time complexity of our approach for the routing is $O(f N E \log K)$, where N is the number of travelers, f is the re-planning fraction (usually 10% in this paper), and $E \log K$ is the complexity of the Dijkstra algorithm where E is the number of edges and K the number of nodes. Note that this is independent of the time resolution. The approaches which re-plan everybody usually exploit the fact that, for any given starting location, one obtains the complete shortest path calculation for *all* destinations with the same worst case complexity as the calculation for just one destination. We thus obtain $O(F(\Delta T) M E \log K)$, where M is the number of possible starting points (traditionally zones) and $F(\Delta T)$ is some function that increases with increasing time resolution (decreasing ΔT) (Chabini, 1998). Since we use each link as a potential starting point, for us this translates into $O(F(\Delta T) E^2 \log K)$. In this paper, where $E \approx 20k$ (every link is a zone), $N \approx 500k$, and $f = 0.1$, the two approaches are about equivalent. For street networks with higher resolution, E grows while N remains constant, making our approach grow more slowly in time complexity.

Also the workplace assignment is an old problem. An example of such a matching is the classic “Hitchcock” solution (Sheffi, 1985), where the workplace assignment is done in such a way that the overall sum of all trip times is minimized. This clearly results in much shorter trips than in reality. Axhausen (1990) suggests to couple demand generation, route assignment, and traffic simulation, although he puts more emphasis on on-trip learning than we have implemented. Several groups such as the groups around Ben-Akiva or Mahmassani are actively working on this as extensions of their ITS projects. We are not aware of any results of these attempts yet. There are also earlier versions of the work presented in this paper (Wagner and Nagel, 1999, Esser and Nagel, 1999).

5 EXPERIMENTAL SETUP

The study described in this paper was carried out as part of the TRANSIMS project (TRANSIMS, 1992), which is currently aimed at simulating the whole city of Portland microscopically (i.e., with resolution down to single individuals) under consideration of activity gen-

eration, modal choice and route planning, and transportation dynamics. The simulations described in this paper were run on a road network consisting of 8,564 nodes and 20,024 links representing a subset of the real network.

Traffic counts are available for 495 links comprising flow data for the morning peak from 7:15am to 8:15am. Data are available for the years 1992 and 1994. We use data for 1992 for those links for which no 1994 data are available (68 links); for all other links, we use the counts of 1994.

The data were collected using pneumatic road tubes and averaged over two or three weekdays; mostly on Tuesdays, Wednesdays, and Thursdays outside of holiday periods and while school was in session. The counts are not seasonally adjusted. Axle adjustment factors are applied to account for trucks, which are not explicitly counted. The accuracy of the counts is considered to be 80 – 85% (Bill Stein, Portland Metro, personal communication).

Another set of data available are the results of assignment runs by Portland Metro. These runs use their own demand generation, and the EMME/2 assignment algorithm (Babin, 1982). We will also use these data to compare with our results. Note that when we talk about “EMME/2” results in the paper, we will mean the results of that particular study by Portland Metro including its demand generation.

A core problem with our census based assignment approach is that trip times are overestimated for at least two reasons:

- (1) First, when people are asked for the time they spend for their trip to work they usually report the total door to door time including the time to get to the car or park the car. On top of that, people tend to overestimate the time they spend driving especially in stop-and-go traffic (K. Lawton, personal communication).
- (2) Second, the road network used for our simulation does not cover most minor streets. That means the time people spend on these roads should be taken out of the distribution.

The amounts of those times can however not be estimated without further information. To get an idea whether a trip time distribution which is shifted to lower trip times yields more realistic results, we did two different workplace assignment iterations: One with the original census distribution, and another with all travel times reduced to 80% of the original value. In the following we refer to these runs as run sim-100 and sim-80, respectively.

In Fig. 2 the total trip time is plotted for both series, sim-100 and sim-80. Each simulation run refers to running the queuing simulation for the morning (from 4am till 12pm). After every 5 iterations in which people are rerouted only, people are assigned to new workplaces. This can be seen as a sudden, normally upward jump of the trip time in the plot. The reason for the jump is that it takes some reroute iterations to adjust the routes to the changes in the trip demand pattern. We ran 20 route iterations after the last workplace assignment to make sure that the routes are actually relaxed.

As expected, the total trip times are lower for sim-80. Yet, it is striking that a decrease in demand by 20% results in relaxed total trip times that are about 50% lower. The reason will be explained in the next paragraph.

By looking at the trip time distributions in the simulation (Fig. 3), it can be seen that the resulting distribution for sim-80 is closer to the corresponding census distribution than it is for sim-100. Even after assignment and route relaxation, there are still a lot of

unrealistically high trip times for sim-100. This results from the fact that the overall traffic demand is more than the network can carry, leading to a lot of congestion. It is well known that large fluctuations occur when transportation systems are operated with demands that exceed capacities (Kelly, 1997; Nagel and Rasmussen, 1994). Actually, detailed investigation shows that in each simulation run different people account for the very high trip times, which underlines the influence of large fluctuations. Also for sim-80, the distribution resulting from the simulation does not perfectly match the corresponding modified census distribution. Nevertheless, the effect of large fluctuations due to congestion is smaller than for sim-100. These erratic occurrences of large trip times are also the reason why the reduction of the demand by 20% leads to a decrease in trip times by 50%: In sim-100, the system is simply not capable to find a solution that is able to match the demand, and thus has too few contributions at trip times around 500 secs while it has too many contributions at trip times above 3000 secs.

As mentioned above, we do not claim that the 80% census trip time distribution leads to a realistic representation of the real traffic flows in the study area. The idea is just to check the assumption that a reduced distribution leads to more realistic traffic flow patterns. The comparison with the field data is topic of the following chapter.

6 SIMULATION RESULTS

First, we compare the field flow data with the results of our simulation runs directly for every link. For comparison, the results of the “EMME/2 study” are also shown. Fig. 4 shows the typical scatterplots, with field data on the x-axis and simulation results for the same links on the y-axis. Note that both axes are logarithmic.

The first observation is that the plots look remarkably similar in structure. All three studies give relatively unbiased results for high flows, and underestimate low volumes. In addition, there are a few data points where simulation and reality are rather far apart.

At closer inspection, one notes that EMME/2 is somewhat overestimating high volumes, whereas our simulations are underestimating them. This is confirmed by bias calculations (see below). Such an effect is consistent with what one would expect: Typical assignment models do not have a flow cutoff at capacity, so that it is possible to actually put more flow on a link than that link has capacity. This happens in particular at bottlenecks on short links in an otherwise relatively uncongested area.³ The queue model traffic simulation which we used for our investigation tends to behave in the opposite way. If demand is higher than capacity, the queue spills back. Once this queue reaches another intersection, that intersection will normally be blocked for all directions, not just for the direction into the congested link. This is a consequence of the fact that the queue model neglects multi-lane effects at intersections. This means, for instance, that a car waiting for a chance to make a left turn blocks all following cars on this link. This tends to cause unrealistically large spill backs.

We already mentioned in the previous chapter that travel demands are overestimated by

³This really depends on the cost function which is used. Most cost functions set link speed v to a very low number (but not to zero) at high volumes. Since link costs $C \propto L/v$, where L link length, we have that congested links do not contribute much to the cost of a route as long as these links are short and rare. In consequence, much too high volumes can be assigned to such links.

using the original census trip time distribution leading to unrealistically large congestion. For that reason, we ran the same iteration series against a modified trip time distribution, where all trip times were reduced to 80%, which corresponds to a 20% reduction in demand. The resulting flows are closer to the field data for high volumes, and farther away for medium flows. It is maybe more striking that demand reduction by as much as 20% changes the resulting flows so little. This adds to the conjecture that measured flows in a network depend as much on the network structure as on the demand structure.

For more detailed information, we looked at links in different classes regarding field data and direction (Table 1). For each class c we calculated the mean absolute and relative bias, i.e.

$$b_{abs,c} = (1/N_c) \sum_i (x_i - \xi_i) = (1/N_c) \left(\sum_i x_i - \sum_i \xi_i \right) \quad \text{and} \quad b_{rel,c} = b_{abs,c} / \langle \xi \rangle_c, \quad (9)$$

the mean deviation from the field data, i.e.

$$d_{abs,c} = (1/N_c) \sum_i |x_i - \xi_i| \quad \text{and} \quad d_{rel,c} = d_{abs,c} / \langle \xi \rangle_c, \quad (10)$$

and the root mean square deviation from the field data, i.e.

$$var_c = \left((1/N_c) \sum_i (x_i - \xi_i)^2 \right)^{1/2} \quad \text{and} \quad \sigma_c = var_c / \langle \xi \rangle_c. \quad (11)$$

Links were classified by visual inspection into links leading towards the Portland downtown area, and all other links. The tables show that our simulations are underestimating the flows on the “other” links more than they are underestimating the flows on the links towards downtown. Visual inspection of the simulations reveals that this is probably a result of too *much* demand of traffic away from the downtown area. This is what one would expect from our simplifications: We are assuming a spatially homogeneous trip time distribution; yet, one would expect that people who live downtown moved there because they have a higher dislike of long trip times than the average population.

Regarding the size classes, we find that sim-100 systematically underestimates volumes except for class 1 (< 250). Sim-80 underestimates less for class 6 (> 1500), underestimates more for all intermediate classes, and is nearly unbiased for class 1. The interpretation of this is that in sim-100, traffic on the major roads is so congested that the routes are pushed onto the smaller streets. The EMME/2 studies, in contrast, systematically over-estimate volumes. Similar to our results, the ratio of traffic on small vs traffic on large roads is too high. Quite possibly, the fastest path search that is used in both approaches makes simulated travelers accept complicated detours on minor streets more easily than in the real world.

Last, one should also remember that the estimated accuracy of the field counts is assumed to be no better than $\pm 15 - 20\%$. We will come back to this point in the discussion.

In summary, one can say the following: Our simulations are far enough progressed to allow tentative comparisons to real world volume counts. The simulations done for this investigation lead to traffic flows with volumes that are somewhat low when compared to reality. Due to the complexity of the approach, there can be many reasons for this, and the systematic analysis of these effects should be the subject of future research.

7 DISCUSSION

The purpose of this study was to couple a simple demand generation method with route assignment and transportation micro-simulation via a computational feedback procedure. We wanted to explore in how far such an approach is feasible, and then out of scientific curiosity and as a benchmark we compared the results with real world data and with existing EMME/2 study results for the same problem. What can one learn from this?

First, we are indeed at a point where it is both methodologically and computationally possible to systematically couple demand generation, route selection, and transportation micro-simulation. Again, this does not automatically mean that this is always the best method; however, it can and thus should be explored as one of many alternatives. Also note again that practitioners have always done some version of this feedback: If an assignment did not generate plausible flows, it was common practice to adjust the trip matrix. The main differences thus are that we do it systematically and computerized, and that we use a micro-simulation instead of a static assignment. — The second result that we get is that for the morning peak, extremely simple assumptions yield results which are comparable results of an EMME/2 study.

The next task in our view should be to separate the influences of the different modules. In addition to the input data, there are four computational modules involved in this study: demand generation, routing, traffic flow simulation, and feedback mechanism. All of these can contribute to variations in the volumes. A systematic study would vary or switch these modules one by one and establish the effect on the volumes. This was, however, beyond the scope of our investigation.

NETWORK DATA: We have used the same network input data as the EMME/2 studies. Errors here should, to a certain extent, show up similarly with both approaches. It seems that at the level of current accuracy, there are no major errors in these files. That belief is reinforced by the fact that Portland Metro has been using these files for many years.

DEMAND GENERATION INPUT DATA: The data used here was: household locations, workplace locations, and distributions of start times and trip times. We cannot estimate the accuracy of those. With regard to trip times, we have already discussed earlier that the trip times from the census most probably over-estimate times on our network, for two reasons: (1) Travelers intuitively calculate the time from door to door, not the time actually on the road. (2) Since many local streets are missing in our network, the time spent in our network should be smaller than the complete time on the road. Indeed, reducing all trip times to 80% (“sim-80”) in our study did not lead to significant changes in volumes and even led to *higher* (and more realistic) volumes on the major streets, adding to the assumption that reported trip times are probably too high. Also, just looking only at home-to-work trips is a simplification in itself. We neglect any traffic besides home-to-work trips, such as deliveries, people returning from night shifts, shopping, leisure, etc. All these will be indispensable in order to understand 24-hour traffic patterns.

VOLUME COUNT DATA: There is a slight inconsistency between the input data and the volume count data: Input relies on the census, which is from 1990, while the volume counts are from 1992 and 1994. At the current point, we expect the effect to be small. Inspection of the data itself shows noticeable growth of some of the counts within that short period of two years, however.

A bigger challenge is the strong variability of the data. In Fig. 5 we plot, where available, the counts from both 1992 and 1994, connected by a line. This shows that the variability of the counts is comparable to the variability of the model results. Although it is not readily visible from that plot, the change of counts is by no means monotonic: The average change (mean bias; see above for definition) from 1992 to 1994 is 14.9%, whereas the average difference (mean error) between 1992 and 1994 is 31.1%. A good understanding of variability will be necessary to make progress.

ROUTING: We assume fastest path routing based on the last iteration. While the result of such an approach is not exactly a Nash Equilibrium, it is assumed to be close. It is not clear if real world traffic actually is in such a state. In fact, both our simulation results and the model results from the Portland Metro study over-state traffic on minor streets, indicating that the simulated travelers are more willing to accept complicated detours than real world travelers. Also, at the moment we do not include any other mode of transportation. For the Portland case, this should for example lead to an over-estimation of car traffic in particular between downtown locations.

TRAFFIC FLOW SIMULATION (also called network loading): As discussed earlier, we think that our traffic flow simulation (the queue model) underestimates volumes. In contrast, traditional assignment network loading usually over-estimates volumes (depending on the cost function).

A heuristic possibility for progress would be to design a traffic flow simulation with a behavior somewhere in between our queue model and the traditional assignment network loading. A more systematic approach would be to use a more realistic micro-simulation in order to exactly pin-point the deficiencies. In that context, it would be interesting to also look at link speeds in order to decide whether low counts are caused by low traffic or by congestion. This data is easy to extract from the simulations, but it typically does not exist for the field. ITS technology will have a significant impact here.

One aspect that we already mentioned earlier in the text but that should be stressed again is that our method unrealistically assumes homogeneity of all aspects of the scenario except for traffic. For example, first we assume that the behavioral function f_{ch} is the same for everybody, and that we can obtain it by averaging both the trip times and the accessibility over the whole population and the whole region. This is clearly a simplifying assumption — for example, one might expect that people living downtown have a stronger dislike of long trip times than the average population. And hopefully such a characteristic would be coupled to the demographics, so that demographics-based methods (such as a discrete choice approach) could pick it up.

Another inhomogeneity in the Portland situation stems from the fact that the part of the metro region which is north of the Columbia river, so-called Clark County, belongs to the State of Washington, while the rest of Portland belongs to the State of Oregon. Many Oregon workers choose to live in Clark County for the lower property taxes and cheaper large-lot housing (an effect of differences in land use policy), despite the congested commute and Oregon income tax. Oregon has one of the highest personal income taxes of the U.S. States, while Washington does not have a State tax on personal income. Oregon personal income tax is also paid by non-Oregon residents as long as they work in Oregon. Thus, there is a substantial tax incentive for those who live in Clark County to also work there. This, however, is often not possible due to a low jobs-housing ratio in Clark County. All this results in a relatively high split between peak and non-peak direction volumes on the

Columbia River bridges. Sales tax is the opposite: There is no sales tax in Oregon while sales taxes in Clark county average 8%. In consequence, retail activity in Clark County is somewhat suppressed by residents' proximity to tax-free shopping in Oregon. For example, there is a major big-box retail area on the Oregon side of the I-5 bridge that owes its existence to the sales tax disparity. (Bill Stein, Portland Metro, personal communication)

This should result in less traffic northbound into Clark county in the morning peak in reality than in our model. This is easy to check since there are only two bridges across the Columbia river. Indeed, with sim-80 we obtain 7473 veh/hour northbound as opposed to 4650 in the field, while southbound the numbers are comparable: 10052 and 9740, respectively. Sim-100 numbers are lower than sim-80 numbers, due to congestion in the model, but have the same tendency.

8 Summary

We have implemented a computational feedback between demand generation and traffic simulation in a real world setting in Portland/Oregon. This was done via a double relaxation loop: an inner loop for relaxation of the route assignment with fixed demand, and an outer loop for relaxation of the demand. Typically, about 70 runs of the traffic micro-simulation are necessary for one relaxed result. We have used data from Portland/Oregon.

For simplicity, we have concentrated on assigning workplaces to workers (whose home locations were given). The challenge was to perform this workplace assignment such that self-consistently the resulting trip times would correspond to the trip time distribution given via census data.

We have demonstrated that with current computational technology and simple models, it is possible to do such studies while retaining microscopic resolution throughout the whole computation. Microscopic resolution here means that each of the about 500 000 travelers and each vehicle are represented individually in each step of the method. Our simulations were run on single CPU workstations; one relaxation series typically took about four days of computer time.

Because of the many simplifications, we did not expect our results to be a good model of reality. Nevertheless, in order to provide a benchmark we compared our results to real world morning peak volume counts from the Portland/Oregon area, and we included results of an older study by Portland Metro using different methods into the comparison. These results are summarized in Fig. 4. We are encouraged that we get so close with so relatively little investment in terms of input data. In fact, input data consists of nothing more but the EMME/2 street network information, some population characteristics from the census (home locations of workers; overall trip time distribution for home-to-work trips; overall trip starting time distribution), and the locations of workplaces. The methodology uses a relaxation algorithm of workplace assignment, a fastest-path routing, and a queuing micro-simulation. Our study demonstrates that such a microscopic approach is both computationally and methodologically feasible even on modest computing hardware, and we expect that the future will bring rapid improvements.

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References

- [1] T.A. Arentze, F. Hofmann, C.H. Joh, and H.J.P. Timmermans. Experiences with developing ALBATROSS: A learning-based transportation oriented simulation system. In *Verkehr und Mobilität*, number 66 in Stadt Region Land, pages 61–70. Institut für Stadtbauwesen, Technical University, Aachen, Germany, 1998.
- [2] K.W. Axhausen. A simultaneous simulation of activity chains. In P.M. Jones, editor, *New Approaches in Dynamic and Activity-based Approaches to Travel Analysis*, pages 206–225. Avebury, Aldershot, 1990.
- [3] A. Babin, M. Florian, L. James-Lefebvre, and H. Spiess. EMME/2: Interactive graphic method for road and transit planning. *Transportation Research Record*, 866:1–9, 1982.
- [4] R. J. Beckman, K. A. Baggerly, and M. D. McKay. Creating synthetic base-line populations. *Transportation Research Part A – Policy and Practice*, 30(6):415–429, 1996.
- [5] M. Ben-Akiva and S. R. Lerman. *Discrete choice analysis*. The MIT Press, Cambridge, MA, 1985.
- [6] J. A. Bottom. PhD thesis, Massachusetts Institute of Technology, Cambridge, MA, in preparation.
- [7] J. L. Bowman. *The day activity schedule approach to travel demand analysis*. PhD thesis, Massachusetts Institute of Technology, Boston, MA, 1998.
- [8] G. D. B. Cameron and C. I. D. Duncan. PARAMICS — Parallel microscopic simulation of road traffic. *J. Supercomputing*, 10(1):25, 1996.
- [9] E. Cascetta and A. Papola. An implicit availability/perception random utility model for path choice. In *Proceedings of TRISTAN III*, volume 2, San Juan, Puerto Rico, June 1998.
- [10] I. Chabini. Discrete dynamic shortest path problems in transportation applications: Complexity and algorithms with optimal run time. *Transportation Research Records*, 1645:170–175, 1998.
- [11] S. T. Doherty and K. W. Axhausen. The development of a unified modelling framework for the household activity-travel scheduling process. In *Verkehr und Mobilität*, number 66 in Stadt Region Land. Institut für Stadtbauwesen, Technical University, Aachen, Germany, 1998.

- [12] DYNAMIT, 1999. Massachusetts Institute of Technology, Cambridge, Massachusetts. See its.mit.edu.
- [13] J. Esser. *Simulation von Stadtverkehr auf der Basis zellularer Automaten*. PhD thesis, University of Duisburg, Germany, 1998. See also www.traffic.uni-duisburg.de.
- [14] J. Esser and K. Nagel. Census-based travel demand generation for transportation simulations. In W. Brilon, F. Huber, M. Schreckenberg, and H. Wallentowitz, editors, *Traffic and Mobility: Simulation – Economics – Environment*, pages 135–148, Aachen, Germany, Sep/Oct 1999.
- [15] C. Gawron. *Simulation-based traffic assignment*. PhD thesis, University of Cologne, Germany, 1998.
- [16] R. R. Jacob, M. V. Marathe, and K. Nagel. A computational study of routing algorithms for realistic transportation networks. *ACM Journal of Experimental Algorithms*, in press. See www.inf.ethz.ch/~nagel/papers.
- [17] T. Kelly. Driver strategy and traffic system performance. *Physica A*, 235:407, 1997.
- [18] H.S. Mahmassani, T. Hu, and R. Jayakrishnan. Dynamic traffic assignment and simulation for advanced network informatics (DYNASMART). In N.H. Gartner and G. Improta, editors, *Urban traffic networks: Dynamic flow modeling and control*. Springer, Berlin/New York, 1995.
- [19] P. Metaxatos, D. Boyce, M. Florian, and I. Constantin. Implementing combined model of origin-destination and route choice in EMME/2 system. *Transportation Research Records*, 1493:57–63, 1995.
- [20] K. Nagel and C.L. Barrett. Using microsimulation feedback for trip adaptation for realistic traffic in Dallas. *International Journal of Modern Physics C*, 8(3):505–526, 1997.
- [21] K. Nagel and S. Rasmussen. Traffic at the edge of chaos. In R. A. Brooks and P. Maes, editors, *Artificial Life IV: Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems*, pages 222–235. MIT Press, Cambridge, MA, 1994.
- [22] H. A. Rakha and M. W. Van Aerde. Comparison of simulation modules of TRANSYT and INTEGRATION models. In *Traffic Flow Theory and Traffic Flow Simulation Models*, volume 1566 of *Transportation Research Record*, pages 1–7. Transportation Research Board, Washington, D.C., 1996.
- [23] M. Rickert. *Traffic simulation on distributed memory computers*. PhD thesis, University of Cologne, Germany, 1998. See www.zpr.uni-koeln.de/~mr/dissertation.
- [24] T. Schwerdtfeger. *Makroskopisches Simulationsmodell für Schnellstraßennetze mit Berücksichtigung von Einzelfahrzeugen (DYNEMO)*. PhD thesis, University of Karlsruhe, Germany, 1987.
- [25] Y. Sheffi. *Urban transportation networks: Equilibrium analysis with mathematical programming methods*. Prentice-Hall, Englewood Cliffs, NJ, USA, 1985.

- [26] P. M. Simon and K. Nagel. Simple queueing model applied to the city of Portland. *International Journal of Modern Physics C*, 10(5):941–960, 1999.
- [27] TRANSIMS, TRansportation ANalysis and SIMulation System, since 1992. See transims.tsasa.lanl.gov.
- [28] VISIM, Planung Transport und Verkehr (PTV) GmbH. See www.ptv.de.
- [29] P. Wagner and K. Nagel. Microscopic modeling of travel demand: Approaching the home-to-work problem. Paper 99 09 19, Transportation Research Board Annual Meeting, Washington, D.C., 1999. Also at www.inf.ethz.ch/~nagel/papers.
- [30] Q. Yang. *A Simulation Laboratory for Evaluation of Dynamic Traffic Management Systems*. PhD thesis, Massachusetts Institute of Technology, 1997. See also its.mit.edu.

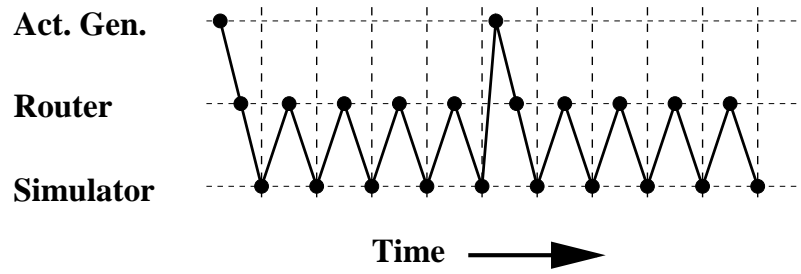


Figure 1: Iterative Activity Re-Assignment: Schematic subsequent application of activity generator, router, and traffic simulator.

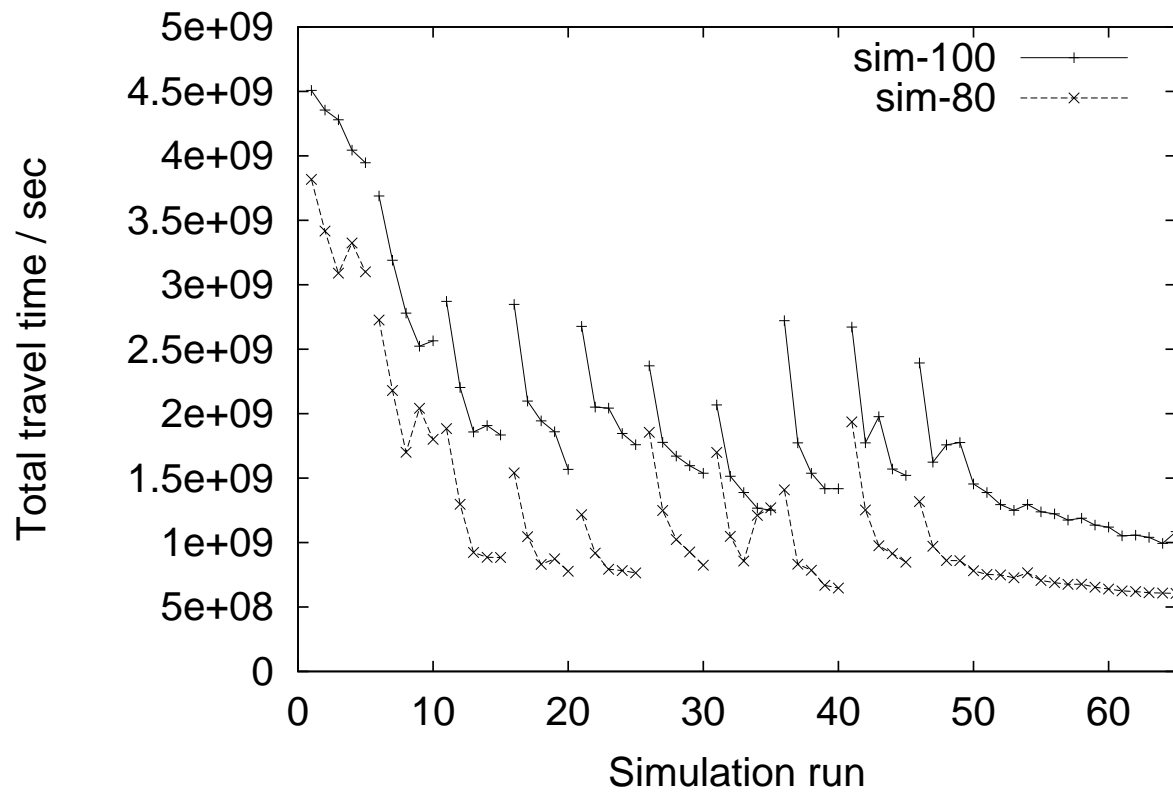


Figure 2: Total trip time in the simulation during the iterative assignment with the original census trip time distribution (sim-100) and the census distribution with trip times reduced to 80% (sim-80).

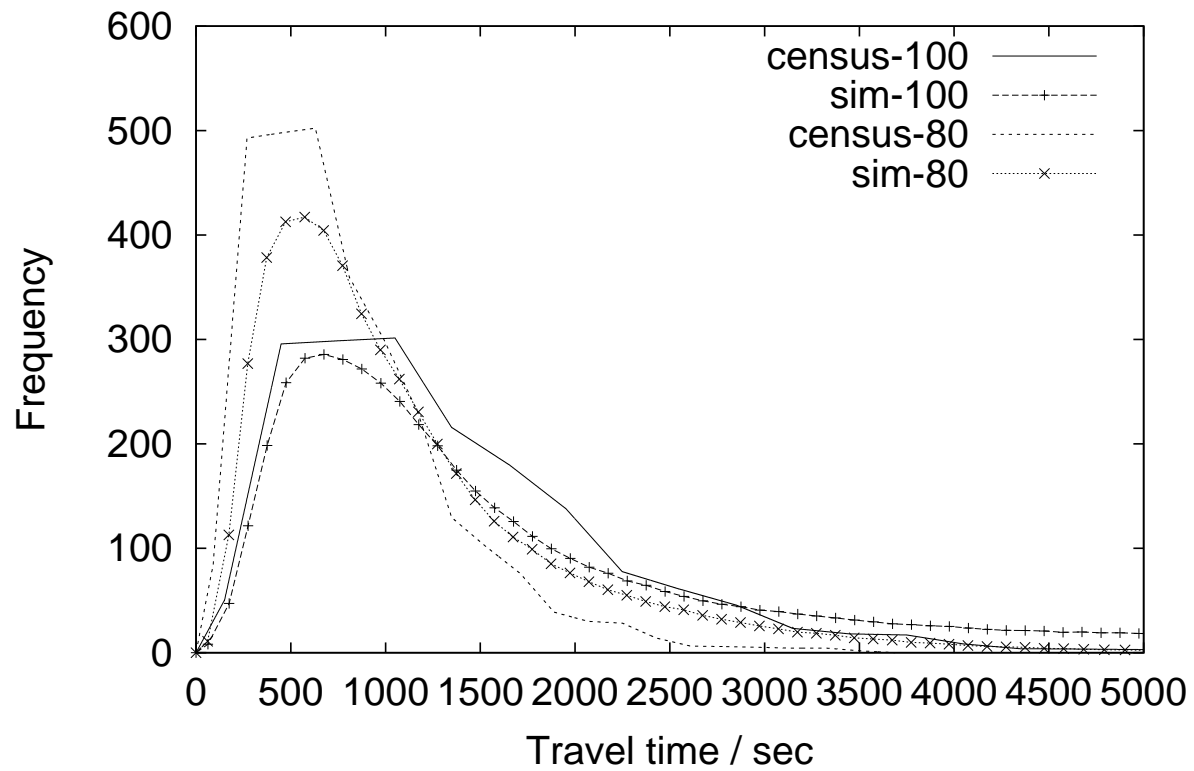


Figure 3: Trip time distributions in the queuing simulation after the 10th workplace assignment and 20 route iterations in comparison to the 100% and the 80% census trip time distribution. Only completed trips contribute to the distribution.

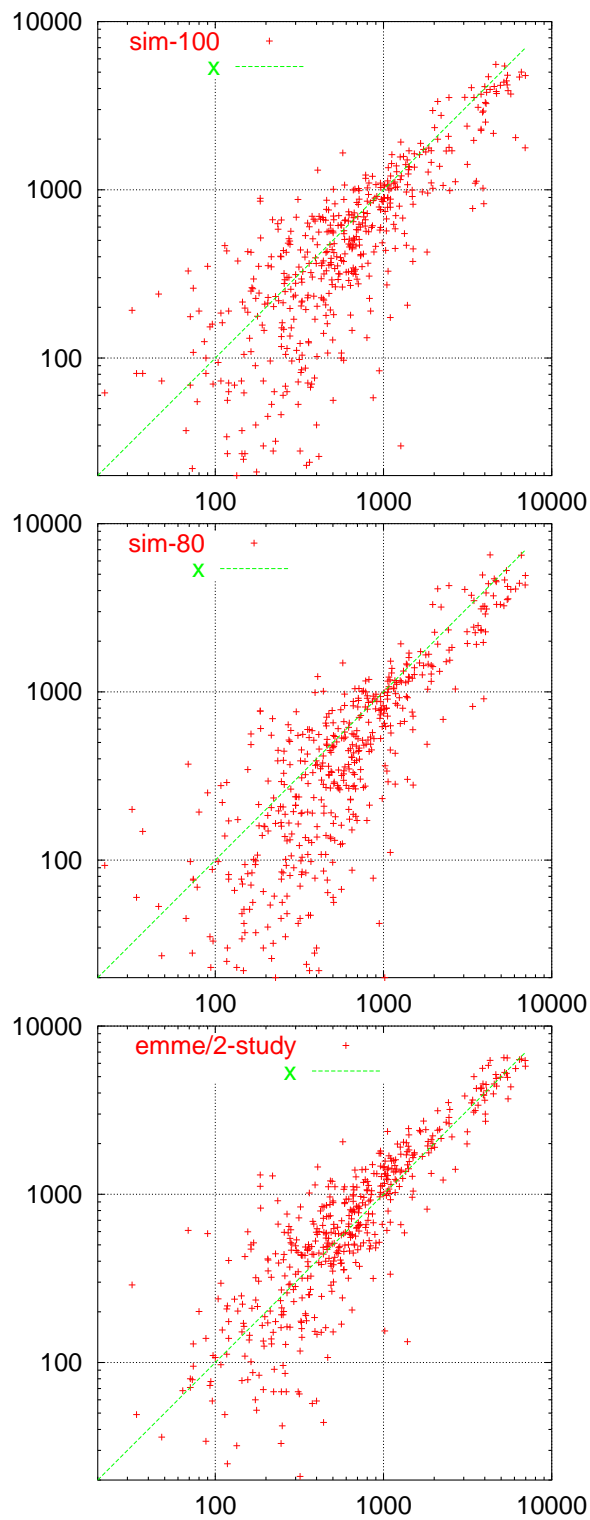


Figure 4: Scatterplot of simulated data (y-axis) vs. field data (x-axis). TOP: sim-100. CENTER: sim-80. BOTTOM: EMME/2-study. It is remarkable that reducing the demand by 20% (top to middle) does not seem to change very much at all.

class	n	mean bias	mean err	RMS err
total	495	-195 (-20%)	342 (36%)	611 (63%)
to-downtown	142	-166 (-15%)	313 (29%)	473 (44%)
other	353	-207 (-23%)	354 (39%)	658 (72%)
< 250	104	46 (32%)	129 (90%)	186 (130%)
250 – 500	126	-51 (-14%)	184 (50%)	226 (61%)
500 – 750	87	-96 (-15%)	226 (37%)	278 (45%)
750 – 1000	44	-184 (-21%)	285 (33%)	367 (43%)
1000 – 1500	62	-274 (-23%)	382 (32%)	512 (43%)
> 1500	71	-855 (-25%)	1068 (31%)	1428 (41%)

class	n	mean bias	mean err	RMS err
total	495	-209 (-22%)	344 (36%)	556 (58%)
to-downtown	142	-191 (-18%)	366 (34%)	575 (53%)
other	353	-216 (-24%)	335 (37%)	548 (60%)
< 250	104	2 (1%)	117 (82%)	167 (116%)
250 – 500	126	-83 (-23%)	200 (54%)	241 (65%)
500 – 750	87	-171 (-28%)	263 (43%)	307 (50%)
750 – 1000	44	-212 (-25%)	291 (34%)	370 (43%)
1000 – 1500	62	-308 (-26%)	388 (32%)	510 (42%)
> 1500	71	-684 (-20%)	1011 (29%)	1249 (36%)

class	n	mean bias	mean err	RMS err
total	495	83 (9%)	275 (29%)	413 (43%)
to-downtown	142	215 (20%)	318 (29%)	476 (44%)
other	353	30 (3%)	258 (28%)	385 (42%)
< 250	104	84 (59%)	146 (102%)	259 (181%)
250 – 500	126	71 (19%)	199 (54%)	263 (71%)
500 – 750	87	57 (9%)	212 (34%)	297 (48%)
750 – 1000	44	106 (12%)	314 (36%)	376 (44%)
1000 – 1500	62	147 (12%)	364 (30%)	473 (39%)
> 1500	71	73 (2%)	574 (16%)	757 (22%)

Table 1: TOP: sim-100. MIDDLE: sim-80. BOTTOM: EMME/2.

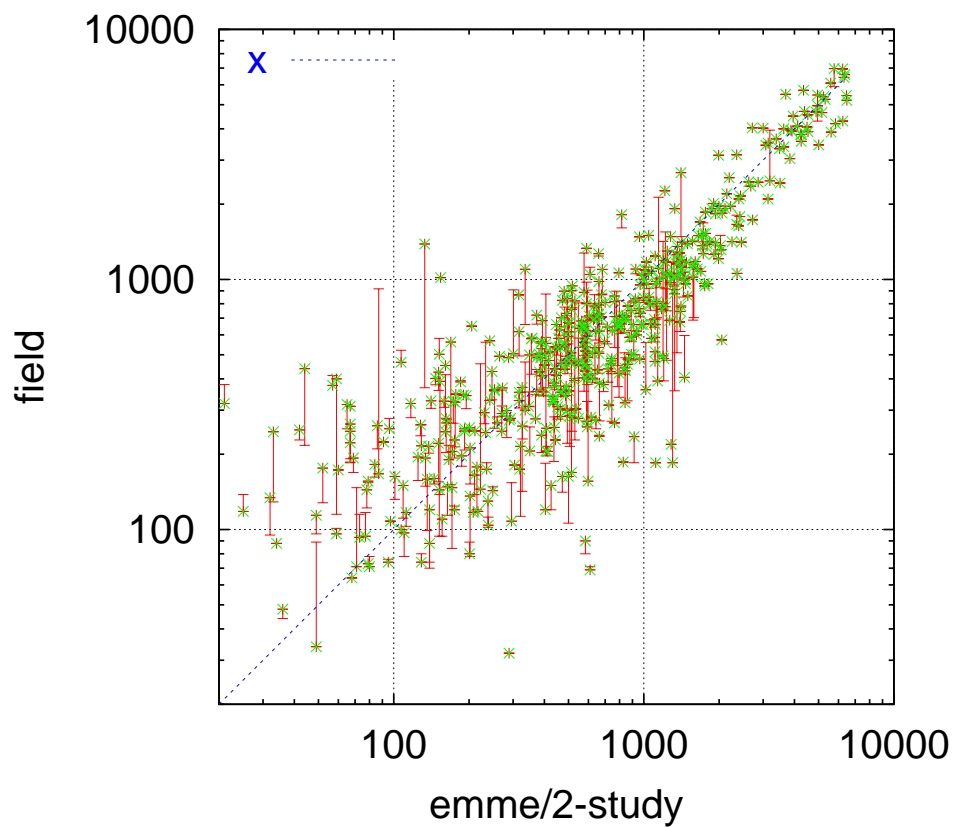


Figure 5: Error ranges of field data. Where available, both the 1992 volume count and the 1994 volume count is plotted. Note that, for technical reasons, this time the model results are on the x-axis and the field data is on the y-axis. A better understanding of field data variability will be necessary for further progress.